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Published in:
I E E E Systems Journal

DOI (link to publication from Publisher):
10.1109/JSYST.2019.2947663

Publication date:
2020

Document Version
Early version, also known as pre-print

Reliability Evaluation in Microgrids with Non-exponential Failure Rates of Power Units

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***Abstract*—This paper explores the impacts of non-exponentially distributed failures on reliability of microgrids. Failure rate of some components such as power electronic converters is not constant, while they play a major role in microgrids. Consequently, their failure characteristics will affect the microgrid reliability. Hence, the conventional reliability evaluation approaches based on Mean Time To Failure (MTTF) may introduce inaccurate inputs for decision-making in planning and operation of microgrids. In this paper, different approaches are employed for evaluating the reliability of microgrids with non-constant failure rates. The obtained results indicate that the system reliability remarkably depends on the failure characteristics and considering mean or steady state probabilities instead of failure statistics may introduce erroneous reliability prediction results. Numerical case studies are provided to illustrate the impacts of failure characteristics on the availability of single power units as well as the reliability of microgrids.**

***Index Terms*—Reliability, Risk, Availability, Exponential failure rate, Non-exponential failure rate, Bathtub shaped failure rate, Adequacy, Wear-out, Microgrid.**

NOMENCLATURE

Acronyms:

MTTF	Mean Time To Failure [year]
MTTR	Mean Time To Repair [year]
LOLE	Loss Of Load Expectation
EENS	Expected Energy Not Supplied
CDF	Cumulative Distribution Function
DC	Direct Current
yr	Year
DG	Distributed Generation
PV	Photovoltaic
FC	Fuel Cell
IC	Interlinking Converter between DC microgrid and grid
μT	Micro-Turbine

Variables:

λ	Failure rate
μ	Repair rate
α	Weibull distribution scale factor
β	Weibull distribution shape factor
ρ	Equivalent transition rates in the method of device of stages
ω	Weight factor for equivalent transition rates in the method of device of Stages
n	Number of equivalent states in the method of device of stages
η	Exponential distribution rate parameter
$\bar{\mu}, \sigma$	Log-normal distribution parameters
Ψ	General CDF
ψ	General PDF
t	Time [year]
h	Hazard function
$\mathbf{P}$	Probability vector of states in Markov process
P_i	Probability of state i in Markov process
$\mathbf{X}$	Stochastic transitional matrix in Markov process
N	Number of states in Markov process
A	Availability
A_i	Availability state i
U	Unavailability
G	Stochastic performance process in semi-Markov process
g_i	Performance of state i in semi-Markov process of G
M	Number of states in semi-Markov process
T_{ij}	Conditional sojourn time in state i if the next state is j
F_{ij}	Conditional sojourn time T_{ij} CDF
T_i	Unconditional sojourn time in state i
$\mathbf{Q}$	Kernel matrix in semi-Markov process
Q_{ij}	Element at the i^{th} row and j^{th} column of $\mathbf{Q}$
ζ_{ij}	Probability of being in state j if the process starts at state I in semi-Markov process
$\bar{p}_j$	Steady state probability of i^{th} state in semi-Markov process
f	Probability density function
$C1$	Condition 1: MTTF = 3.3 and MTTR = 0.05 yr
$C2$	Condition 2: MTTF = 6.6 and MTTR = 0.10 yr
CP_i	Available generation capacity in i^{th} day of year
L_i	Peak load in i^{th} day of year
LL_i	Load level based on generation capacity
d_i	Number of days the system load stays in the range of LL_i
E_i	Energy Curtailed in i^{th} day of year

I. INTRODUCTION

GRID modernization is essential to ensure reliable and secure power delivery with low to zero carbon emmision. It requires deploying new technologies and infrastructure and also deregulating the electricity sector. Some established technologies have a significant role in modernizing power systems including distributed generations especially

This work was supported by the Reliable Power Electronic-Based Power System (REPEPS) project at the Department of Energy Technology, Aalborg University as a part of the Villum Investigator Program funded by the Villum Foundation.

renewable resources, distributed energy storages, electronic distribution systems and electric vehicles [1]. Microgrids and smart-grids provide suitable infrastrucure for integrating and operating such thechnologies [2]–[4]. Notably, power electronics plays an underpinning role in energy conversion process of aforementioned technologies [1]. Howevre, increasing use of power electronics poses new challenges to reliable planning and operation of power systmes.

Reliability evaluation in power systems is of main concern for power system planners and operators. Any decision-making in design, planning, operation, and maintenance of power systems requires appropriate assessment tools, component reliability models, and component reliability data. Approximate assessment approaches, inaccurate reliability models and data may cause non-optimal decision making or unreliable design and planning consequences. However, lack of reliability models and data together with the complexity of large power systems have been the main challenges for power system engineers [5]. Hence, justified approximations have been performed to analyze the reliability of such a complex and large system [6], [7]. Furthermore, the average values of reliability data such as MTTF and MTTR are typically utilized [2], [5], [7]–[10] in power system reliability assessment.

In modern power systems especially in microgrids, power electronic converters are one of the main components, while they are prone to non-exponential failures including infant mortality and wear-out failures [11]–[16]. Furthermore, power switches and capacitors are the most fragile components of power converters [17]–[21] which are prone to wear-out failures. These components, in many cases, are not repairable. Hence, they will be replaced with a new one whenever they fail according to, e.g., a run-to-failure replacement strategy. As a result, their failure characteristics not only is non-constant (due to the wear-out failures), but also depends on a time to failure which is a random variable. Therefore, using expected values of failure characteristics for reliability and risk assessment may cause erroneous results and consequently non-optimal decision-making for design, planning and operation of power systems.

The impact of non-constant failure/repair rates on a component reliability has been studied in [6], [22]–[31]. In [24], [25], the concept of availability prediction considering time-dependent failure/repair rates in a general system has been presented. In [6], [22], [28], the impact of non-exponential down-time (non-constant repair rate) on the power system reliability has been addressed. However, the failure rate of components has been assumed to be constant. Furthermore, in [6], [28], the steady state availability values have been employed for system reliability analysis. Moreover, a Weibull-Markov model is presented in [29], [30] for evaluating the reliability of power systems with non-constant transition rates. In this approach, even non-constant failure/repair rates are employed, the steady state probabilities are used for reliability assessment in power systems. However, the instantaneous availability may be higher or lower than its steady state value in the early lifetime, which introduces erroneous reliability prediction for some time periods.

A piece-wise approximation of a time-varying failure function has been employed in [23], [27], [31], where the failure rate is considered to be constant in discrete time slots. However, the failure function may be changed if a failure happens at any time. This issue will introduce high reliability prediction error in power converters since its components will be replaced by a new one in the case of failure occurrence.

Furthermore, the aging failures has been incorporated in the power system reliability assessment in [26]. In [26], the availability of a components is predicted based on two types of failures including repairable and ageing failures. The availability due to the repairable failure is predicted based on Markov model. Moreover, the availability of the aging failure is estimated based on the posteriori probability function, which is the probability of failure at any time period after instant t given that the component has survived until t [26]. In this approach, it is assumed that the components aging remains over the operation period and the component has survived until t. However, it has not been addressed how to predict the availability if the component fails at any random time before t, and how to incorporate the replacement rate in the availability prediction.

Therefore, according to the state-of-the-art research, incorporating the non-exponential failures in power system analysis are classified into two categories: (1) the non-exponential failures impact is considered at the steady state values of component availability, e.g., in [6], [28]–[30], (2) the increasing aging process impact on the component availability without considering the component replacement, e.g., in [23], [26], [27], [31]. As a result, both categories cannot accurately model the availability of components which are prone to non-exponential failures such as power converters. Therefore, the decision-making based on aforementioned approaches may cause erroneous results.

Thereby, this paper explores the impact of non-exponentially distributed failures including early life, useful life and wear-out failures on the reliability of power systems. Different failure characteristics are considered modeling the infant mortality, wear-out and random failures. The power units availability is evaluated using different approaches including Markov model based on MTTF values, method of devise of stages, semi-Markov model, and steady state semi-Markov model. Moreover, the well-known power system reliability indices as LOLE and EENS are employed to evaluate the reliability of a microgrid. In the following, Section II presents the different approaches predicting the power unit availability. Numerical case studies are provided in Section III to compare the system availability employing different approaches and illustrate the impacts of non-constant failure rates on single unit availability. The effect of non-constant failure rates on a microgrid reliability and risk is explored in Section IV for a two-unit generation microgrid. Furthermore, Section V explores the impact of converter wear-out failure on the reliability of a DC microgrid with different energy sources. Finally, the outcomes are summarized in Section VI.

II. AVAILABILITY MODELING

The term availability is used to predict the probability in which a repairable component is found in the operating state at some time t in the future given that it started in the operating state at t = 0. This probability depends on the failure and repair rate of component. For exponential failure and repair distributions, the availability is directly calculated by Markov chain. However, availability of systems with non-exponential failure rate cannot be calculated by Markov methods. Hence, other methods such as devise of stages and semi-Markov approach should be employed. This section introduces three methods for availability calculation in repairable systems which are Markov chain, device of stages and semi- Markov approach.

A. Markov approach – conventional approach

This method is applicable for the components/systems with the constant (exponential) failure and repair rates. The state space model of a single unit component is shown in Fig. 1 where departure rates of λ and μ are the failure and repair rates respectively.

In a general case, with N states, the probability of each state can be found by using:

$$\begin{aligned}&\frac{d}{dt}\mathbf{P}(t)=\mathbf{P}(t)\mathbf{X}\\&\mathbf{P}(t)=\left[P_1(t),\,P_2(t),\,\ldots,\,P_N(t)\right]\end{aligned}\,, \tag{1}$$

where, $\mathbf{P}(t)$ is a vector of instantaneous state probabilities and $\mathbf{X}$ is a stochastic transitional matrix as:

$$\mathbf{X}=\left[X_{ij}\right]$$
$$X_{ij}=\begin{cases}-\sum\limits_{\substack{j=1\\ j\neq i}}^{n}X_{ij} & i=j\\ \text{departure rate from state '}i\text{' to state '}j\text{'} & i\neq j\end{cases}\,. \tag{2}$$

For a single unit system shown in Fig. 1, the probability of states 1 and 2 can be obtained as:

$$\begin{aligned}p_1(t)&=\frac{\lambda}{\lambda+\mu}+\exp\left(-(\lambda+\mu)t\right)\left(P_1(0)\frac{\mu}{\lambda+\mu}-P_2(0)\frac{\lambda}{\lambda+\mu}\right)\\ p_2(t)&=\frac{\mu}{\lambda+\mu}+\exp\left(-(\lambda+\mu)t\right)\left(P_2(0)\frac{\lambda}{\lambda+\mu}-P_1(0)\frac{\mu}{\lambda+\mu}\right)\end{aligned}\,. \tag{3}$$

Hence, the availability of the system is the probability of being in UP state which is equal to $P_2(t)$ as:

$$A(t)=P_2(t)\,. \tag{4}$$

Hence, the steady state availability can be found from the limiting state probability of Up state as:

$$A=P_2(\infty)=\frac{\mu}{\lambda+\mu}\,. \tag{5}$$

B. Method of device of stages

If a state has a non-exponential distribution, it can be divided into some exponentially distributed states, where the number of states, way of their connection and the distribution function parameters can be defined by Method of stages [28]. According to this approach, non-exponential repair rate in the system given in Fig. 1 can be represented by a set of

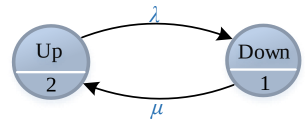

Fig. 1. State space Markov model of single unit.

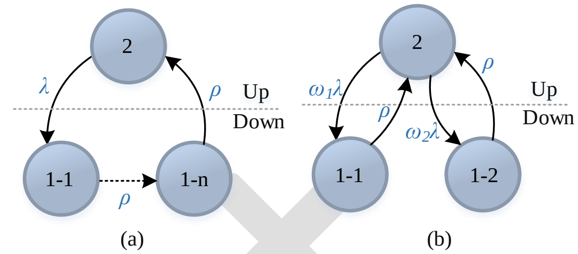

Fig. 2. Decomposition of non-exponential repair rate to; (a) stages in series with Weibull distribution with shape factor $\beta \geq 1$, (b) stages in parallel with Weibull distribution with shape factor $\beta \leq 1$.

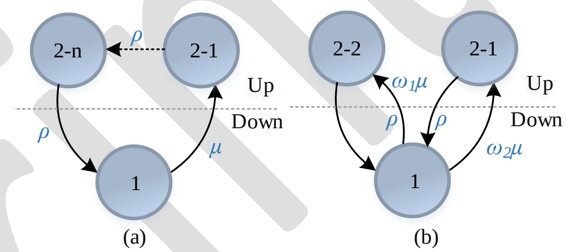

Fig. 3. Decomposition of non-exponential failure rate to; (a) stages in series with Weibull distribution with shape factor $\beta \geq 1$, (b) stages in parallel with Weibull distribution with shape factor $\beta \leq 1$.

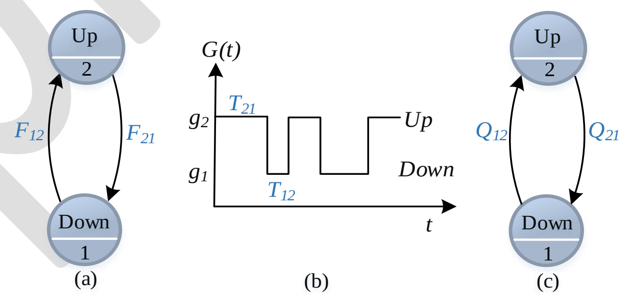

Fig. 4. State space representation of a single unit, (a) state transition model, (b) semi-Markov stochastic process, (c) semi-Markov model.

exponentially distributed stages, where the series connection is used for Weibull distribution with shape factor $\beta \geq 1$ as shown in Fig. 2(a), and parallel connection is used for Weibull distribution with $\beta \leq 1$ as shown in Fig. 2(b) [6]. Where the parameters n, number of stages, ρ, departure rate of stages, ω_1 and ω_2, the probability of being in stage 1-1 and 1-2, can be found by matching the first two moments of Weibull distribution and the distribution of sum of n exponential distributions [6].

This approach is applied in this paper for the systems with non-exponential failure rates as shown in Fig. 3. After decomposing the states into exponential stages, the probability of each state can be obtained similar to the Marko approach represented by (1) and (2). Furthermore, the probability of Up or Down state will be found by adding up the probability of the corresponding stages.

C. Semi-Markov approach

Semi-Markov process is another approach to model and analyze the availability of non-exponentially distributed systems [32], [33]. Consider a system with two states of Up and Down as shown in Fig. 4(a) with a stochastic performance process of $G(t) = \{g_1, g_2\}$. The system remains in state $i = \{1, 2\}$ with random time of T_{ij}, $j = \{1, 2\}$, $j \neq i$, and CDF of $F_{ij}(t)$, which is conditional sojourn time in state i if the next state is j. A graphical representation of this process is shown in Fig. 4(b). In the semi-Markov process, the sojourn times T_{ij} can be arbitrary distributed while the time between transitions must exponentially be distributed.

In order to analyze the semi-Markov process, kernel matrix **Q** can be defined as (6), where Q_{ij} is the one-step transition probability from state i to state j as given in (7). For instance, the state space representation of the semi-Markov model for stochastic process $G(t)$ with two states is shown in Fig. 4(c). The corresponding kernel matrix Q is given in (8), where Q_{12} and Q_{21} can be calculated using (9) according to the CDF of sojourn times at states 1 and 2. F_{ij} is the CDF of sojourn time at state i under condition that it transfers to state j.

$$\mathbf{Q}(t) = \left[Q_{ij}(t)\right] \tag{6}$$

$$Q_{ij}(t) = \text{Probability}\left\{\left(T_{ij} \le t\right) \& \left(\forall_{\substack{k \neq j \\ 'k'\text{ connected to }'i'}} T_{ik} \ge t\right)\right\} \tag{7}$$

$$\mathbf{Q}(t) = \begin{bmatrix} 0 & Q_{12}(t) \\ Q_{21}(t) & 0 \end{bmatrix} \tag{8}$$

where,

$$\begin{aligned} Q_{12}(t) &= \text{Probability}\left\{\left(T_{12} \le t\right)\right\} = F_{12}(t) \\ Q_{21}(t) &= \text{Probability}\left\{\left(T_{21} \le t\right)\right\} = F_{21}(t) \end{aligned} . \tag{9}$$

The probability of being in state j if the process starts at state i, ζ_{ij} can be obtained as [32]:

$$\zeta_{ij}(t) = \delta_{ij}\left(1 - F_i(t)\right) + \sum_{k=1}^{2} \int_0^t \frac{d}{d\tau} Q_{ik}(\tau) \cdot \zeta_{kj}(\tau - t)\, d\tau \tag{10}$$

where δ_{ij} is:

$$\delta_{ij} = \begin{cases} 1 & i = j \\ 0 & i \neq j \end{cases} . \tag{11}$$

F_i is the unconditional sojourn time CDF in state i which can be found as:

$$F_i = \sum_{j=1}^{n} Q_{ij} . \tag{12}$$

Finally, if the successful states of system include the states k, $k+1, \ldots, M$ and the state M being the initial state, the instantaneous availability $A(t,k)$ of the system at any instant t is found by:

$$A(t,k) = \sum_{j=k}^{M} \zeta_{Nj}(t) . \tag{13}$$

For instance, the availability of single-unit system shown in Fig. 4(a) is the probability of state 2 as:

$$A(t,k) = \zeta_{22}(t) . \tag{14}$$

D. Steady-state semi-Markov approach

The steady state availability of each state is found by:

$$A(k) = \frac{\bar{p}_k T_k}{\sum_j \bar{p}_j T_j} , \tag{15}$$

where T_j is the expected value of the unconditional sojourn time in state j. $\bar{p}_j$ is the steady state probability of the state j in the semi-Markov process [32], [33].

III. Availability Of a Single-Unit System

This section provides numerical analysis to illustrate the viability of different approaches in availability prediction.

Furthermore, the system availability under non-exponential failure rates are illustrated and compared with the conventional approach considering constant failure rates. Three distribution functions are considered including Exponential, Weibull and Lognormal distributions as reported in TABLE I. In the following studies, two conditions are considered as; C1) MTTF = 3.3 and MTTR = 0.05 yr, and C2) MTTF = 6.6 and MTTR = 0.1 yr. Under both conditions the system has an identical limiting state availability defined as (16) if the system is exponentially distributed.

$$A = \frac{MTTF}{MTTR + MTTF} \tag{16}$$

In the following, three cases are considered with different failure characteristics for C1 and C2.

1) Exponential failure rate

In this case, exponential failure rates are considered and the system availability is calculated employing the three introduced approaches. As shown in Fig. 5, the availability of semi-Markov, devise of stages and conventional approaches are identical. Furthermore, the steady state availabilities under conditions C1 and C2 are the same. The transient behavior is different; however, the settling times are almost negligible. Hence, for exponential failures the steady state probabilities can be used for availability and risk analysis.

2) Non-exponential failure rate – wear-out

In this case, the system availability under wear-out failure characteristics are calculated and shown in Fig. 6. The solid and dashed lines show the results under two conditions of C1 and C2 respectively. C1 and C2 respectively model the wear-out failures with Weibull distribution in TABLE I (α_1 = 3.76, β_1 = 2.2) and (α_2 = 7.45, β_2 = 3). If the failure rates are considered to be constant and equal to the reciprocal of the corresponding distribution MTTF, the availability approaches

TABLE I
Failure density functions

Distribution	Density function	CDF
Exponential	$\psi(t) = \eta \exp(-\eta t)$	$\Psi(t) = 1 - \exp(-\eta t)$
Weibull	$\psi(t) = \frac{\beta t^{\beta-1}}{\alpha^{\beta}} \exp\left(-\left(t/a\right)^{\beta}\right)$	$\Psi(t) = 1 - \exp\left(-\left(t/a\right)^{\beta}\right)$
Lognormal	$\psi(t) = \frac{1}{t\sigma\sqrt{2\pi}} \exp\left(\frac{\left(\ln(t) - \bar{\mu}\right)^2}{2\sigma^2}\right)$	$\Psi(t) = \frac{1}{2} + \frac{1}{2} erf\left(\frac{\ln(t) - \bar{\mu}}{\sqrt{2}\sigma}\right)$

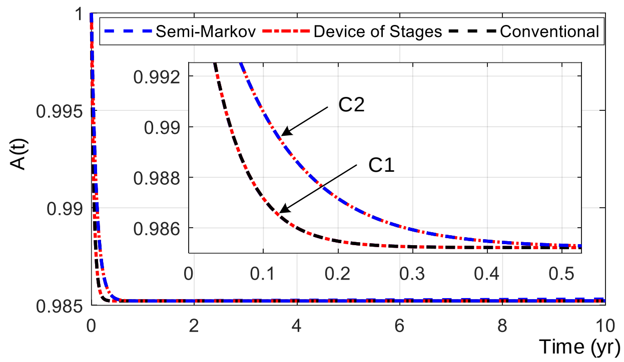

Fig. 5. Availability of single-unit system with exponential failure rate – C1: MTTF = 3.3, MTTR = 0.05, C2: MTTF = 6.6, MTTR = 0.1.

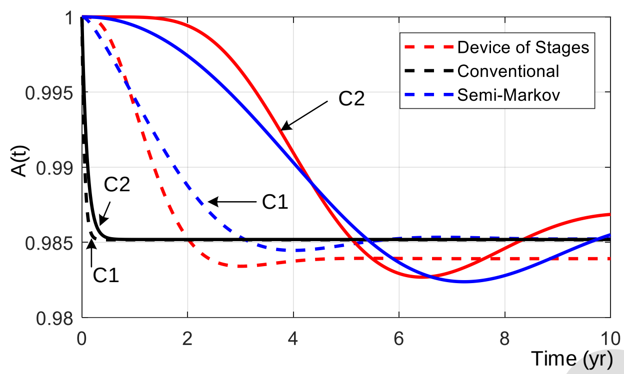

Fig. 6. Availability of single-unit system with non-exponential failure rate modeling wear-out with Weibull distribution for C1(α_1 = 3.76, β_1 = 2.2) and C2 (α_2 = 7.45, β_2 = 3).

the steady state in a very short time as shown in Fig. 6. While in device of stages considering stages in series with an exponential failure rate , according to [6], the settling time will be almost 3 and 9 years under conditions C1 and C2 respectively. Furthermore, the semi-Markov approach also gives similar results. The small variation between semi-Markov and device of stages comes from approximating the non-exponential distribution with some series of exponentially distributed stages. However, the obtained results shown in Fig. 6 imply that the instantaneous availability in the case of non-constant failure rate has different behavior during transients. Consequently, employing the steady state availability for reliability and risk analysis imposes unnecessary cost of risk in the case of non-exponential failure rates.

3) *Non-exponential failure rate – early lifetime*

In this case, the system availability is calculated considering early lifetime failure under condition C1 with Weibull distribution (α_1 = 2.21, β_1 = 0.6). The three approaches are compared in Fig. 7. Semi-Markov and device of stages show that the instantaneous availability is lower than the one obtained by assuming constant failure rate. Furthermore, the transient response of availability employing the device of stages is different from the semi-Markov result. This fact is due to the approximation in modeling the non-exponential distributed stages in parallel according to [6].

Furthermore, the system availability considering three different distributions modeling the early lifetime failures are

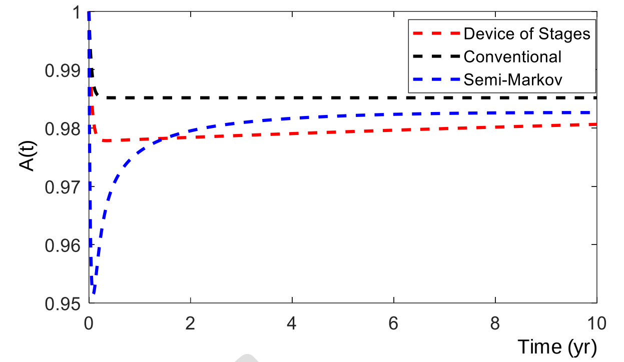

Fig. 7. Availability of single-unit system with wear-out failure rate of Weibull distribution for C1(α_1 = 2.21, β_1 = 0.6).

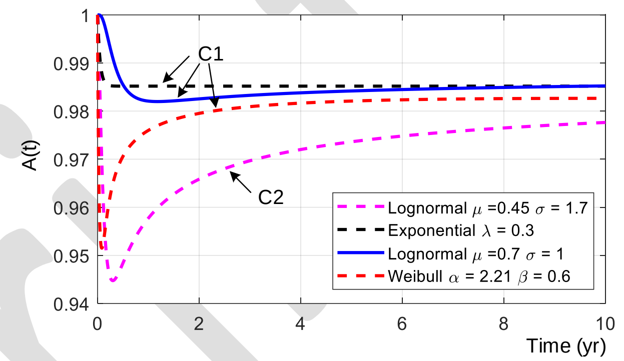

Fig. 8. Availability of single-unit system employing semi-Markov approach with non-exponential failure rates modeling early lifetime failures.

shown in Fig. 8. This figure shows that the system availability significantly depends on the failure distribution function. For instance, under lognormal distribution (μ = 0.7, σ = 1), the availability is very close to the corresponding exponential distribution, while Weibull distribution causes much difference within transient period as well as at steady state. Moreover, comparing the results of the two lognormal distributions shows that the failure distribution can significantly affect the system reliability. Therefore, considering early lifetime failures to be exponentially distributed, the designed system may not be reliable since the actual availability will be lower than its exponential counterpart.

This section illustrates the impact of non-constant failure rates on the single-unit availability. Obtained results shows that assuming constant failure rates can either impose unnecessary cost of risks or result in unreliable designed system. Furthermore, the results show that the Markov proves is a suitable approach for availably prediction of systems with constant failure/repair rates. Even the introduced methods give the same results, the Markov process is a straight forward solution. However, in the case of non-constant failure/repair rates, employing the Markov process with expected values of failure/repair rates causes remarkable availability prediction error. Hence, the method of device of stages and semi-Markov approach can be used for availability prediction in these cases. Meanwhile, the method of device of stages may cause small error due to the approximating the non-exponential distribution function with combination of exponential distribution functions. Therefore, if higher reliability prediction is required, the semi-Markov approach should be employed even though it is a time-consuming process specially for large scale systems. Moreover, the method of device of stages with low calculation burden can be employed if the induced error is acceptable. Furthermore, for the units with different failure mechanisms, the availability associated with each mechanism can be predicted based on the failure characteristics. For instance, a power converter may have three major failure mechanisms including failure of power switch, capacitor and cooling system. The power switch and capacitor availabilities can be predicted by semi-Markov approach since they are prone to wear-out failures, while the cooling system availability can be estimated by Markov process due to its constant failure rate. In the following, the impact of different non-exponential failures on the system-level reliability of microgrids is illustrated.

IV. Failure Characteristics Impact on Two-Unit Generation System Reliability

This section evaluates the adequacy of a two-unit generation microgrid as shown in Fig. 9 with different failure characteristics. From generation system adequacy point of view, the system load can be aggregated in a single bus connected to the generation units, and the other components can be assumed to be fully reliable [7]. The microgrid reliability studies aim to evaluate the generation capacity adequacy to supply the load with a minimum level of loss of load which is called adequacy evaluation.

A. Adequacy evaluation

The term adequacy is associated with the existence of sufficient generation facilities to satisfy the grid demand. The most useful adequacy measurement is Loss Of Load Expectations (LOLE) which is the number of days/hours within a period of time the grid demand cannot be supplied due to the generation shortage [34]. LOLE can be calculated as [7], [34]:

$$LOLE = \sum_{i=1}^{n} P_i\left(CP_i - L_i\right) \tag{17}$$

where, CP_i is the available generation capacity, L_i is the peak load and $P_i(CP_i\text{-}L_i)$ is the probability of loss of load in the i^{th} day. For instance, the Markov representation of a two-generation system with two 50 kW units is shown in Fig. 10. According to this model, the system risk, LOLE can be calculated as:

$$LOLE = d_1\left(1 - A_3\right) + d_2\left(1 - A_2 - A_3\right) \tag{18}$$

where, d_1 and d_2 are the number of days during a year that the grid demand stays in 50 $kW \le LL_1 \le$ 100 kW and 0 $kW \le LL_2 <$ 50 kW respectively. A load model is provided in Fig. 9 and employed in this section for LOLE analysis.

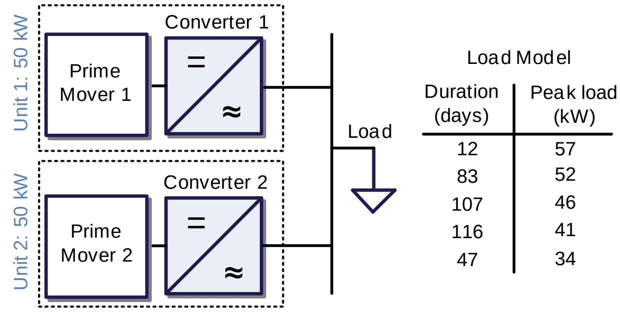

Fig. 9. Single line diagram of a two identical unit-based microgrid.

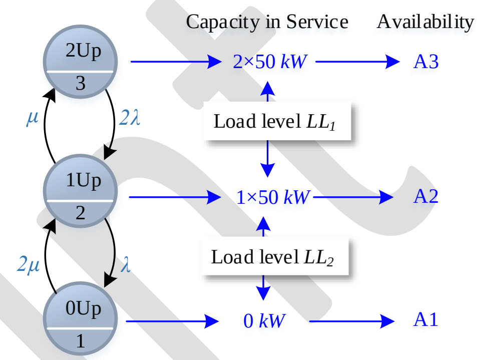

Fig. 10. State space representation of two-unit generation system.

TABLE II
DISTRIBUTION FUNCTION PARAMETERS

Failure Shape	Function	Distribution	MTTF = 6.6 MTTR = 0.1	MTTF = 3.3 MTTR = 0.05
	$f_1(t)$	*Weibull*	α = 2.5, β = 0.7	α = 0.1, β = 0.9
Bathtub	$f_2(t)$	*Exponential*	η = 0.135	η = 0.48
	$f_3(t)$	*Weibull*	α = 10, β = 7	α = 8.5, β = 5
Random	$f_4(t)$	*Exponential*	η = 0.15	η = 0.3
Wear-out	$f_5(t)$	*Weibull*	α = 10, β = 5	-
	$f_6(t)$	*Exponential*	η = 0.245	-
Early lifetime 1	$f_7(t)$	*Lognormal*	$\bar{\mu}$= 0.615, σ =1.6	$\bar{\mu}$ = 0.2, σ =1.1
	$f_8(t)$	*Exponential*	-	η = 0.23
Early lifetime 2	$f_9(t)$	*Weibull*	α = 2.5, β = 0.7	α = 0.5, β = 0.7
	$f_{10}(t)$	*Exponential*	η = 0.1	η = 0.166

In the following, different failure characteristics are assumed for the generation units and the system risk is calculated. These failure characteristics are shown in Fig. 11. The MTTF of failure distributions are considered to be 0.15 and 0.3 failure/year and the corresponding repair rates are selected to be 10 and 20 repair/year. The reason of choosing these repair rates is to carry out a fair comparison amongst different alternatives, since they give the same limiting state availability if the MTTF and MTTR are employed for risk assessment like the conventional approach. The failure distributions employed in this study are explained in the following.

B. Failure characteristics

Bathtub shaped failure: most of system components generally have failure rate characteristics like the one shown in Fig. 11(a) known as bathtub curve, in which the failure rate is decreasing in the early lifetime which models the infant mortality failures. The second part is constant and associated with the random failures. In the last part, the increasing failure rate is related to the wear-out failure. The failure density function is defined as:

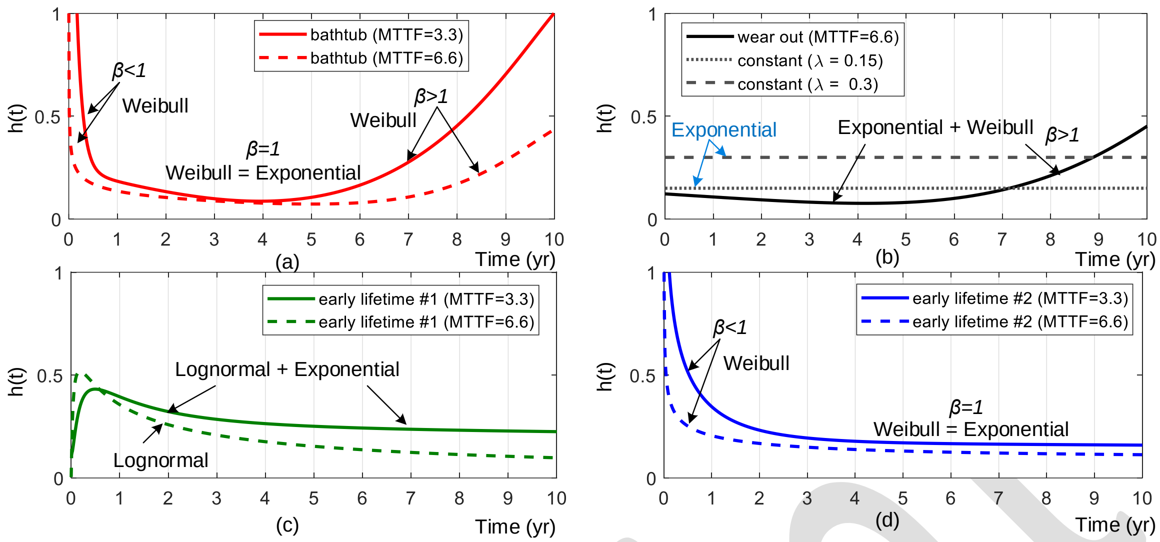

Fig. 11. Hazard rate of units, (a) bathtub shaped failure, (b) wear-out and constant failure, (c) Lognormal based early lifetime failure, and (d) Weibull based early lifetime failure.

$$f(t)=\tfrac{1}{3}\left(f_1(t)+f_2(t)+f_3(t)\right) \tag{19}$$

where, $f_1(t)$, $f_2(t)$, $f_3(t)$ are given in TABLE II.

Random failure: In most engineering systems, it is considered that the system is working in the middle part of bathtub curve, where it faces the random failures associated with sever and unpredictable stresses arising from sudden environmental shocks. These failures are exponentially distributed as (20), and $f_4(t)$ is given in TABLE II.

$$f(t)=f_4(t) \tag{20}$$

Wear-out failure: Increasing failure rates in wear-out phase is a result of depletion process due to the abrasion fatigue and creep on the device or system components. It can be modeled by Weibull distribution (β >1). In some cases, such as power electronic converters [11], the system faces the random and wear-out failures due to the degradation of its fragile components during operation. The failure rate of such systems is modeled by (21) where $f_5(t)$ and $f_6(t)$ are the Weibull and Exponential distributions as given in TABLE II.

$$f(t)=\tfrac{1}{2}\left(f_5(t)+f_6(t)\right) \tag{21}$$

Early lifetime failure: In some cases, such as wind turbine systems, the failure rates are decreasing during operation [12]–[15]. The failure of such systems are modeled by (22)-(24). In (22), $f_7(t)$ is a lognormal distribution with the parameters given in TABLE II.

$$f(t)=f_7(t) \tag{22}$$

Furthermore, the failure density function given in (23) models the early lifetime and random failures with lognormal and exponential distributions. The functions of $f_7(t)$, $f_8(t)$ are defined in TABLE II.

$$f(t)=\tfrac{1}{2}\left(f_7(t)+f_8(t)\right) \tag{23}$$

Another failure density function is considered as (24) where early lifetime failures are modeled by $f_9(t)$ as Weibull distribution (β <1) and $f_{10}(t)$ as random failures by exponential distribution as summarized in TABLE II.

$$f(t)=\tfrac{1}{2}\left(f_9(t)+f_{10}(t)\right) \tag{24}$$

C. *Numerical analysis and discussion*

Considering the non-constant failure rates, the state space representation of the system is shown in Fig. 12(a), where F_{ij} is the CDF of sojourn time in state i in which the system transits to state j. F_{12} and F_{23} are the exponentially distributed repair CDFs with repair rate of 2μ and μ respectively where μ is the reciprocal of MTTR given in TABLE II. F_{32} is the failure CDF in which one out of two units fails and F_{21} is the failure CDF if anther operating unit fails. The relation between failure density functions in TABLE II with F_{32} and F_{21} are explained in the Appendix. Employing the failure density functions, the kernel matrix can be obtained by (6) according to the semi-Markov model represented in Fig. 12(b). Hence the system availability, employing semi-Markov process for the two-unit system is calculated based on (13). Furthermore, the system risk LOLE is obtained by (17). The obtained results are explained in the following.

The instantaneous availability of state 3 (A_3), in which both units are Up, is shown in Fig. 13 for different failure characteristics. These results imply that the instantaneous availabilities of different failure characteristics diverge from the availability of constant (exponential) failure rate even though they have the same MTTF and MTTR. Furthermore, the availability of state 2 (A_2) in which one out of two units is Up, is shown in Fig. 14. According to the results illustrated in Fig. 13 and Fig. 14, the availability of a system with non-constant failure rate remarkably depends on the failure distribution. Furthermore, estimating the system availability using MTTF of the failure distribution causes significant error on the outcomes.

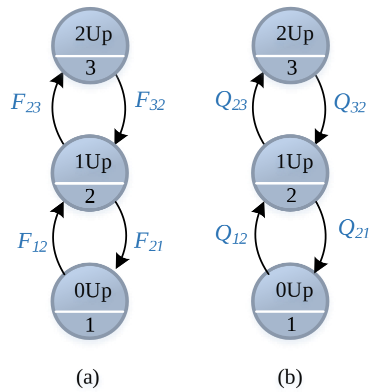

Fig. 12. State space representation of two-unit generation system, (a) state transition model with non-exponential failure rates, and (b) semi-Markov model.

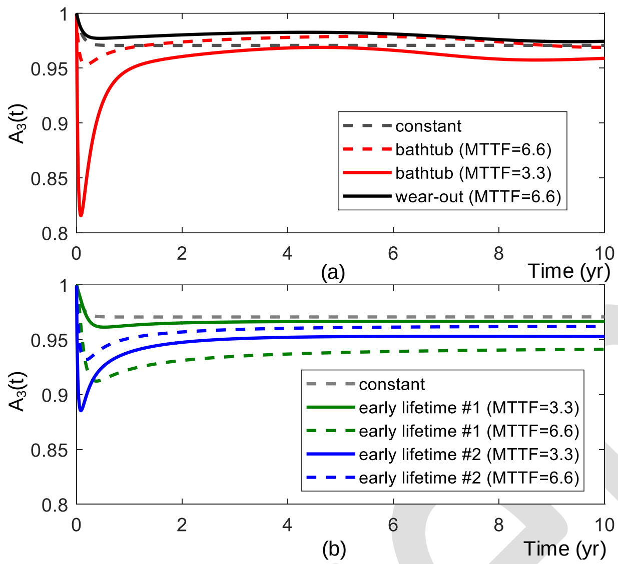

Fig. 13. Instantaneous availability of state 3: both of units are Up; impact of (a) bathtub failure and wear-out, (b) early lifetime failure.

The LOLE of the two-unit microgrid with different failure distributions is calculated based on (17). Since the annual load model is utilized, hence, the LOLE is estimated at the end of each year according to the minimum availability of system states during that year. The obtained results are shown in Fig. 15. The interpretation of the results is provided in the following.

a) The system LOLE with constant failure rates is equal to 2.86 days/year. As shown in Fig. 15, the LOLE with exponential failure rate has a constant value during operating time. This fact is due to the short transient time of availabilities in this case as shown in Fig. 13 and Fig. 14 given for constant failure rate.

b) According to [6], the steady state availability values for a system having non-exponential distributions are identical to those with exponential distributions. However, according to Fig. 13 and Fig. 14, the steady state values of availabilities are not identical for different failure distributions. Moreover, the transient time of some distributions are quite longer than that of constant failure rate. Therefore, estimating the LOLE of non-exponentially distributed systems based on the limiting state probabilities of its exponential counterpart, will not provide accurate risk values. This fact is shown in Fig. 15 implying that the LOLE of non-exponential distributions is less or more than the exponential one depending on the failure characteristics. As a consequence, risk assessment and management based on assuming constant failure rates may not guarantee having a reliable system. Therefore, any decision making in planning, operation and maintenance of power systems require accurate reliability and risk analysis.

c) Instead of limiting state probabilities of corresponding exponentially distributed failures discussed in (b), one may use the steady state probabilities of semi-Markov approach in (15). These steady state values have been written by blue in each case in Fig. 15. It can be seen that the steady state values provide an under-/over-estimated risk values based on the failure characteristics.

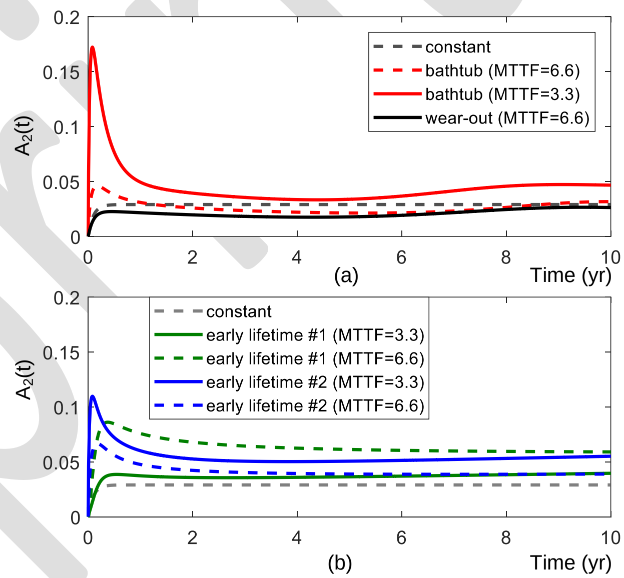

Fig. 14. Instantaneous availability of state 2: one out of two units is Down; impact of (a) bathtub failure and wear-out, (b) early lifetime failure.

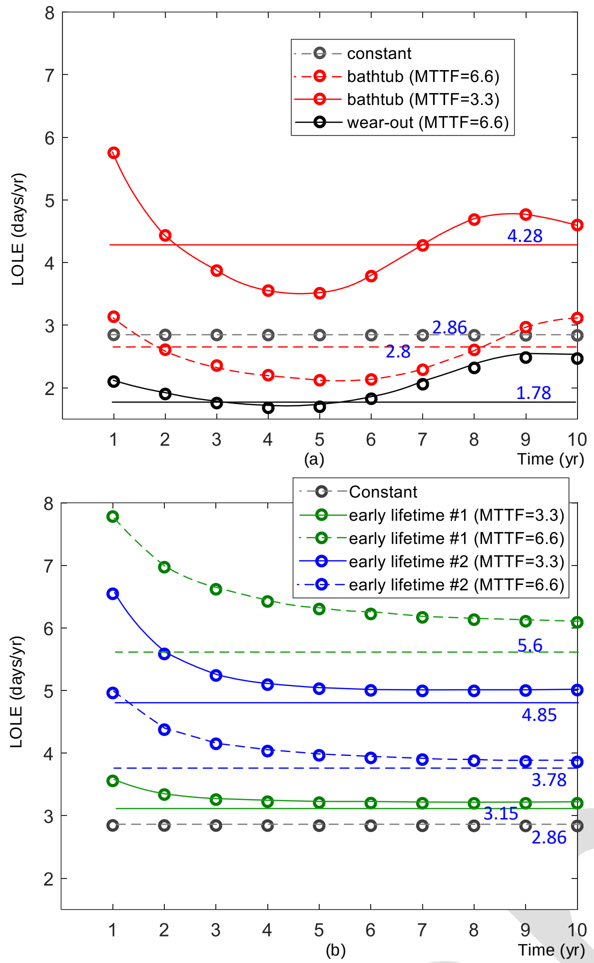

Fig. 15. LOLE of 2-unit microgrid with the failure rates given in Fig. 11; impact of (a) bathtub shape hazard rate and wear out, (b) early lifetime failure.

d) The system risk (LOLE) under non-exponential failure rates remarkably depends on the failure distribution. For instance, the LOLE under failure characteristics of wear-out is lower than the LOLE of constant failure rate. Moreover, the system risk in the case of bathtub shaped failure with MTTF of 6.6 year is sometime higher and sometime less than the exponential one. In other cases, the system risk is notably greater than the exponentially distributed failures.

e) According to the illustrated results in Fig. 15, the LOLE is proportional to the failure rates. For instants, the failure rate of bathtub shaped distributions is high in the early and end lifetime as shown in Fig. 11(a) consequently, the system risk is also high in these periods as illustrated in Fig. 15(a). Moreover, in the early lifetime failure distributions given in Fig. 11(c) and (d), the high failure rates in early lifetime results in high LOLE in the same period as shown in Fig. 15(b).

V. Reliability of a Power Electronic Based Microgrid

In this section, the impact of converter wear-out failure on the reliability of a DC microgrid is predicted according to the generation system adequacy concept. The generation system adequacy can be measured by LOLE as defined in (17), which is the number of hours per year that the demand cannot be supplied due to the generation shortage. Furthermore, the amount of energy curtailed, E_i, due to the generation capacity shortage can be used as another index of adequacy, which is defined as:

$$EENS = \sum_{i=1}^{n} P_i \cdot E_i \ . \tag{25}$$

The DC microgrid is shown in Fig. 16 which comprises different energy resources including a 30 kW PV, 2×25 kW FC, one 40 kW µT. Furthermore, it is connected to the grid through a 50 kW IC converter. Moreover, the annual load variation curve, so-called load duration curve, is model by a straight line joining the 130 kW of maximum peak load and the 40 kW of minimum peak load as shown in Fig. 16. The PV system contains four strings with 26 series connected 285-W PV panels per each string. The output power of PV system is predicted according to EN 50530:2010 [35] employing measured solar irradiance and ambient temperature in Arizona (see Fig. 17 (a and b)). For generation system adequacy evaluation, the output power of PV system is divided into 15 levels, and the annual probability of each power level is shown in Fig. 17 (c).

The failure and repair data of the DGs are summarized in TABLE III. Furthermore, the failure rate of converters for different DGs are shown in Fig. 18. The availability of each generation unit including its prime mover and converter is obtained by Markov process and semi-Markov approach respectively. Fig. 19 shows the DGs unavailability function with constant failure rates as well as taking into account the aging of converters. The aging failure is modeled by the Weibull distribution as summarized in TABLE III. The converter's aging characteristics is assumed to be the same for all DGs for the sake of comparison. As shown in Fig. 19, the wear-out of converters will affect the converter unavailability. In order to illustrate the impact of converter aging on the system-level reliability, the LOLE and EENS are estimated according to (17) and (25).

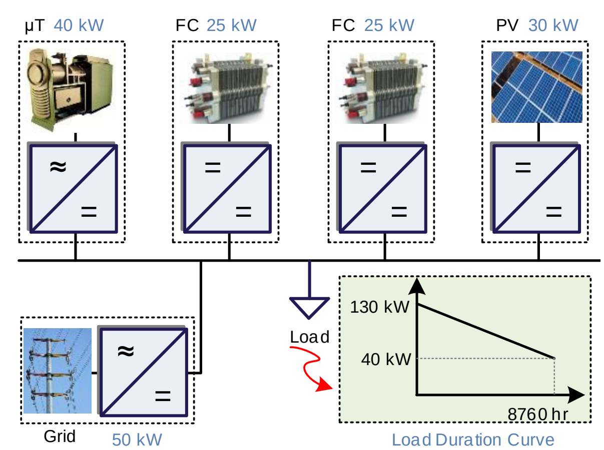

Fig. 16. Single line diagram of a DC microgrid.

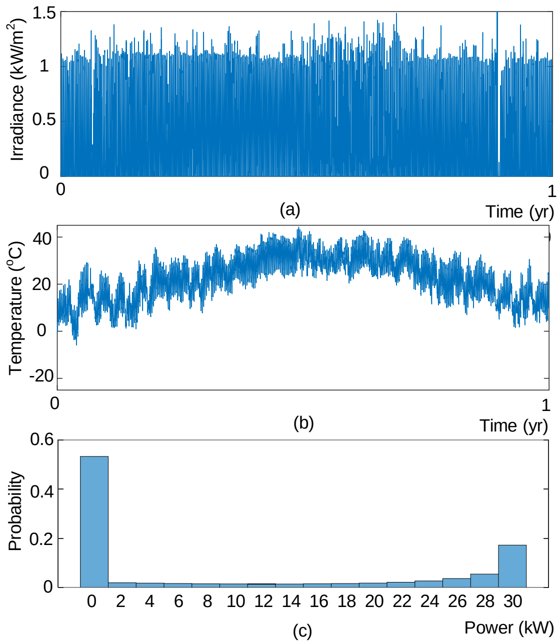

Fig. 17. Annual mission profiles of (a) solar irradiance, (b) ambient temperature, and (c) probability of PV system output power.

TABLE III
DGs and Converters Reliability Data

DG	Prime Mover		Converter		
Failure type	*Constant failure rate [f/yr]*	*Repair time [hr]*	*Constant failure rate [f/yr]*	*Wear out failure parameters* (α [yr], β)*	*Repair time [hr]*
PV	*0.15*	*80*	*0.35*	*7, 3.5*	*100*
FC	0.20	150	*0.15*	*7, 3.5*	*100*
IC	1.00	5	*0.20*	*7, 3.5*	*100*
µT	0.30	200	*0.25*	*7, 3.5*	*100*

**Wear-out failure is modeled by the Weibull distribution function.*

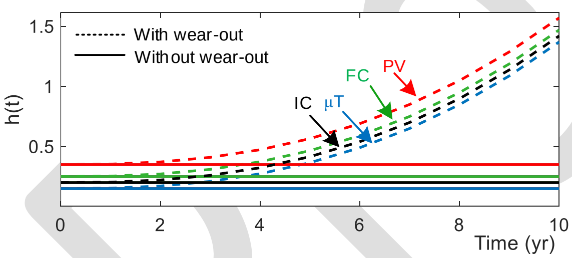

Fig. 18. Failure rate of converters for different DGs in the DC microgrid shown in Fig. 16 with and without converter wear-out.

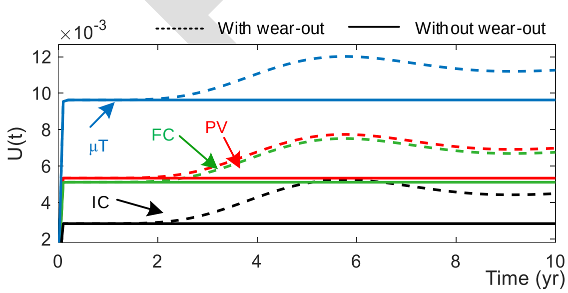

Fig. 19. Total unavailability of DGs (converter and prime mover) in the DC microgrid shown in Fig. 16.

Fig. 20 shows the system level reliability indices of microgrid considering the impact of individual converter wearing-out and the aging of all converters. Following Fig. 20, the microgrid reliability indices LOLE = 7.8 hr/yr and EENS = 46.7 kWh/yr considering constant failure rate of the DGs as a base case. As shown in Fig. 20, the PV and FC converters aging have almost negligible impact on the LOLE and EENS. This is due to the fact that the probability of output power of PV at different power level is quite low as shown in Fig. 17 (c). Moreover, the capacity of each FC unit is lower than others, and hence, its impact on system reliability is not considerable. The aging of µT converter and IC can increase the LOLE by 1.2 hr/yr and 2.2 hr/yr as shown in Fig. 20 (a), which can remarkably affect the system reliability depending on the application of microgrid. Furthermore, the EENS due to the µT converter aging is quite low as shown in Fig. 20 (b), while the IC can increase the EENS by 23 kWhr/yr which is almost 150% of the base case. This is due to the fact that the IC has the largest capacity in the system. Considering the aging of all of the converters, the LOLE will be increased by 3.7 hr/yr and the EENS will be increased by 34 kWhr/yr as shown in Fig. 20.

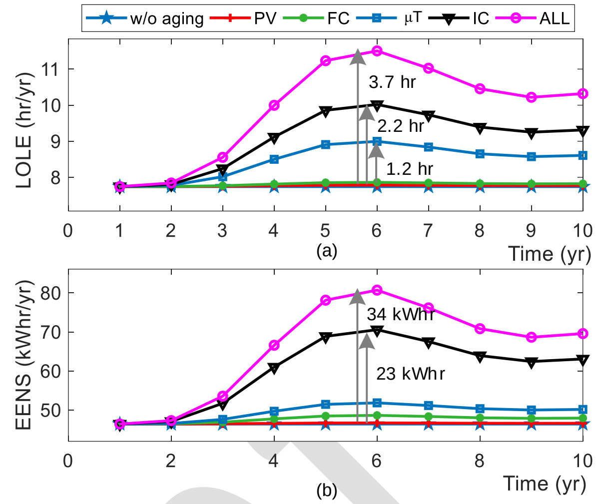

Fig. 20. Obtained system-level reliability indices in the DC microgrid shown in Fig. 16 considering wear-out of individual converters and all converters; (a) LOLE and (b) EENS. (w/o: without)

As a result, the aging of converters can remarkably affect the microgrid reliability depending on their applications. For instance, the PV converter aging impact on LOLE and EENS is negligible. However, the IC aging has the highest impact on the system reliability. Therefore, the accurate reliability modeling of converters as one of the fragile components of microgrids is of high importance for microgrid design and planning. Employing the constant failure rates of components may cause inaccurate reliability estimation, and consequently non-optimal decision-making. Especially, for some applications such as more-electric air crafts and hospitals, the accurate reliability modeling is a must.

VI. Conclusion

This paper has explored the impact of non-exponentially distributed failures on the microgrid reliability. Different reliability modeling approaches have been presented, and the availability of a single power unit with different failure characteristics has been investigated. Obtained results show that the availability of non-exponentially distributed systems is not identical to the corresponding exponentially distributed system with the same expected time to failure and repair. Therefore, employing MTTF values in system reliability analysis will introduce inaccurate results.

Furthermore, the adequacy of a microgrid with non-exponential failure rates has been evaluated employing LOLE and EENS based risk indices. The obtained results show that the LOLE and EENS significantly depend on the failure characteristics, and hence, employing MTTF based availability or semi-Markov steady state availability may cause erroneous reliability and risk results. Hence, optimal decision-making for planning and operation of microgrids with high penetration of non-exponentially distributed units, i.e., power converters requires considering the corresponding failure characteristics. The future work will focus on extending the time-dependent reliability assessment of a large-scale power electronic based power systems.

VII. Appendix

The state space representation of a two-unit system is shown in Fig. 21(a). As the units have the same capacity, in order to reduce the calculation burden, the states b and c – in which one out of the two units is Down – can be merged to one state, i.e., state 2, as shown in Fig. 21(b). Following the definition given in Section II.C, F'_{32} is the CDF of sojourn time in state 3 if the next state is state 2. The probability of transition from state 3 to state 1 considering the failure of only one unit can be obtained by:

$$F'_{32}(t) = Probability\{T_1 < t, T_2 > t\} + Probability\{T_2 > t, T_1 < t\} \quad (26)$$

where T_1 and T_2 are random sojourn times in state 3 if the system transits to state b and c respectively. The probabilities in (26) can be calculated by the sojourn times CDF in state 3 as:

$$F'_{32}(t) = \int_0^t dF_{3b}(u) \int_t^\infty dF_{3c}(u) + \int_0^t dF_{3c}(u) \int_t^\infty dF_{3b}(u) \quad (27)$$

Considering the same density functions for T_1 and T_2 as (28), the F'_{32} can be obtained as (29).

$$F(t) = F_{3b}(t) = F_{3c}(t) \quad (28)$$

$$F'_{32}(t) = 2\int_0^t \left(1 - F(u)\right) dF(u) = 2F(t) - F^2(t) \quad (29)$$

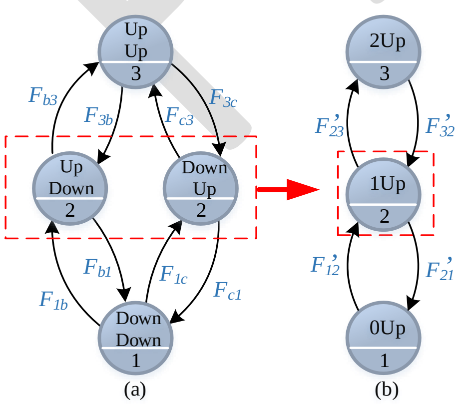

Fig. 21. State space representation of two-unit generation system, (a) Markov model with exponential failure rates, (b) semi-Markov model.

Similarly, F'_{12} can be obtained by CDF of transitions from state 1 to b and c. Moreover, F'_{21} is the CDF of sojourn time in state 2 given that it will transit to state 1. The sojourn time in state 2 is equal to the time being in states b and c where the next state is 1. Therefore, F'_{21} is defined as (30):

$$\begin{aligned} F'_{21}(t) &= \text{Probability}\{T_3 < t, \text{Unit 2 is Down}\} \\ &\quad + \text{Probability}\{T_4 < t, \text{Unit 1 is Down}\} \\ &= 0.5\int_0^t dF_{b1}(u) + 0.5\int_0^t dF_{c1}(u) \end{aligned} \quad (30)$$

where T_3 and T_4 are random sojourn times in state b and c respectively under the condition that 1 is the next state. Considering same density functions for T_3 and T_4 as (31), the F'_{21} can be obtained as (32).

$$F(t) = F_{c1}(t) = F_{b1}(t) \quad (31)$$

$$F'_{21}(t) = F(t) \quad (32)$$

Similarly, F'_{23} can be obtained by CDF of transitions from state b and c to 3.

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